REMARKS

I. INTRODUCTION

In view of the foregoing amendments and the following remarks, Applicants respectfully request reconsideration and allowance of the present application.

II. OBJECTIONS TO THE DRAWINGS

The drawings have been amended per the Examiner's requests in paragraphs 3 and 4 of the Office Action. More specifically, Figures 2 and 4 have been amended to include a legend with the terms "Prior Art." Figures 4, 6A and 6B have been amended to clarify the labels of the elements in the figures. Three replacement sheets are attached hereto for these changes.

III. OBJECTIONS TO THE SPECIFICATION

Amendments to the specification follow the suggestions of the Examiner in paragraphs 7 and 8 of the Office Action.

III. CLAIM REJECTIONS

A. <u>Claim Rejections Under 35 U.S.C. §112</u>

All claims rejected for failing to comply with the written description requirement have been cancelled, except for claim 16, which has been amended. Applicants respectfully submit that claim 16, as amended, complies with the written description requirement, and support for the claim 16, as amended, can be found starting at page 15, line 31 of the specification.

AMENDMENTS TO THE DRAWINGS

Please approve the following changes to the drawings. The drawings have been amended per the Examiner's requests in paragraphs 3 and 4 of the Office Action. More specifically, Figures 2 and 4 have been amended to include a legend with the terms "Prior Art." Figures 4, 6A and 6B have been amended to clarify the labels of the elements in the figures. Three replacement sheets are attached hereto for these changes.

B. Claim Interpretation

Applicants concur with Examiner's definition of "cumulative density function".

Applicants respectfully decline Examiner's interpretation with respect to claims 16 and 41. Rather than meaning that more densely populated data is sampled at a higher frequency, Applicants note that the specification makes sufficiently clear (*e.g.*, at page 15, starting at line 31) that for parameters that are known to drive the system being modeled, a finer range or bin interval is used so that such a parameter dictates more of the vectors chosen for training. Since whole vectors are being chosen (*e.g.*, FIG. 5), no parameter (also referred to as vector element) necessarily is included with any greater frequency than any other (indeed, each vector must have values for all the sensors), but *which* vectors are included is dictated more by the parameter deemed to be a driver.

C. Claim Rejections Under 35 U.S.C. §102(b)

Claims 1, 3, 4, 6-8, 10-32, 34 and 36-49 stand rejected under 35 U.S.C. §102(b) as being anticipated by U.S. Patent Number 5,809,490 to Guiver. Applicants concur that Guiver is addressing a similar problem to that solved in the present invention, namely selecting a subset of all available historic data, and doing so in a manner that provides better representation of sparse data in the model. As in the present invention, the data being selected in Guiver takes the form of contemporaneous snapshots of multiple parameters, forming multidimensional input vectors. However, Guiver discloses *clustering* the p-dimensional vectors in p-space (see, *e.g.*, col. 7, starting at line 1), associating each historic available vector with a cluster, and sampling members of the clusters for training purposes. All of

the methods disclosed by Guiver, including SOM, k-means clustering, and LVQ (col. 10, lines 61-65) are *multidimensional* clusterizers.

In contrast, the present invention does not attempt to cluster the available historic vectors and, furthermore, does not cluster them multidimensionally. Each dimension of the data vectors is treated separately, which, among other advantages, allows important "driver" parameters to be covered by a finer sampling of training vectors than less important non-driver parameters. Furthermore, according to the present invention, the sampling of vectors for training is performed iteratively over each variable or parameter. This is not disclosed in or otherwise suggested by Guiver.

For clarity, Applicants reiterate that though vector inclusion in training data is being carried out by examining the ordered values of a single given sensor across all vectors, when a value indicates inclusion, the entire vector is included.

The methods disclosed or otherwise taught by Guiver would result in potentially quite different data being selected for training than would be selected by the present invention. For example, if the data treated by Guiver's methods happened to strongly cluster on account of one variable, even while the other variables possessed some variation, the cluster might be underrepresented in the training data from the perspective of these other variables. But, in the present invention, variation in these other variables would not be masked by the strongly grouped variable, since each dimension is treated separately.

Turning specifically to claim 1, Guiver does not disclose or otherwise suggest "ordering the set of training vectors according to a corresponding value in each vector", since the methods of Guiver are cluterizers. Ordering in the present invention is according to a univariate function of just one measured parameter serving as an element in the vectors. After ordering, the vectors are divided by

equally spaced ranges on that ordering. The ordering, as in claim 4, can be by magnitude, or alternatively, as in claim 6, by cumulative density function. Note that ordering is not the same as clustering, as a vector that might belong to a cluster in the clusterizing approach, may very well belong to a different range adjacent to the cluster, if the range boundary runs through or near the cluster.

In claim 8, regularly spaced intervals along the ordering of the observations according to the values of a particular sensor is different from clustering as disclosed in or otherwise taught by Guiver.

In claim 13 (now amended) the system vectors are ordered and, then, assigned to bins according to said ordering using the measure of a selected parameter (again univariate). Thus, the bins are defined with respect to the order of the selected parameter, which would again give potentially different results from a clusterizer as taught in Guiver.

In claim 32, program code orders the vectors according the value of a particular sensor, and additional program code divides the total range for that sensor into equally spaced ranges to which the vectors are assigned. This is likewise different from clustering as taught in Guiver.

D. Claim Rejections Under 35 U.S.C. §103(a)

Claims 2, 5, 9, 33 and 35 stand rejected under 35 U.S.C. §103(a) based on Guiver in view of U.S. Patent Number 5,764,509 to Gross et al. Gross relates to the modeling technique described by the Applicants, and discloses the Min-Max training technique. However, Gross does not provide any teaching or motivation to make up for the differences between Guiver (multidimensional clustering) versus the present invention (univariate ordering/binning). Therefore, it would not be

obvious to one skilled in the art to derive the present invention from Guiver in view of Gross.

V. CONCLUSION

In view of the foregoing, Applicants respectfully request reconsideration and allowance of this application. More specifically, as demonstrated above, independent claims 1, 8, 13, 26 and 32, and their respective dependent claims, are respectfully submitted as being in condition for allowance.

Respectfully submitted,
FITCH, EVEN, TABIN & FLANNERY

By Mark W. Hetzler
Mark W. Hetzler
Registration No. 38,183

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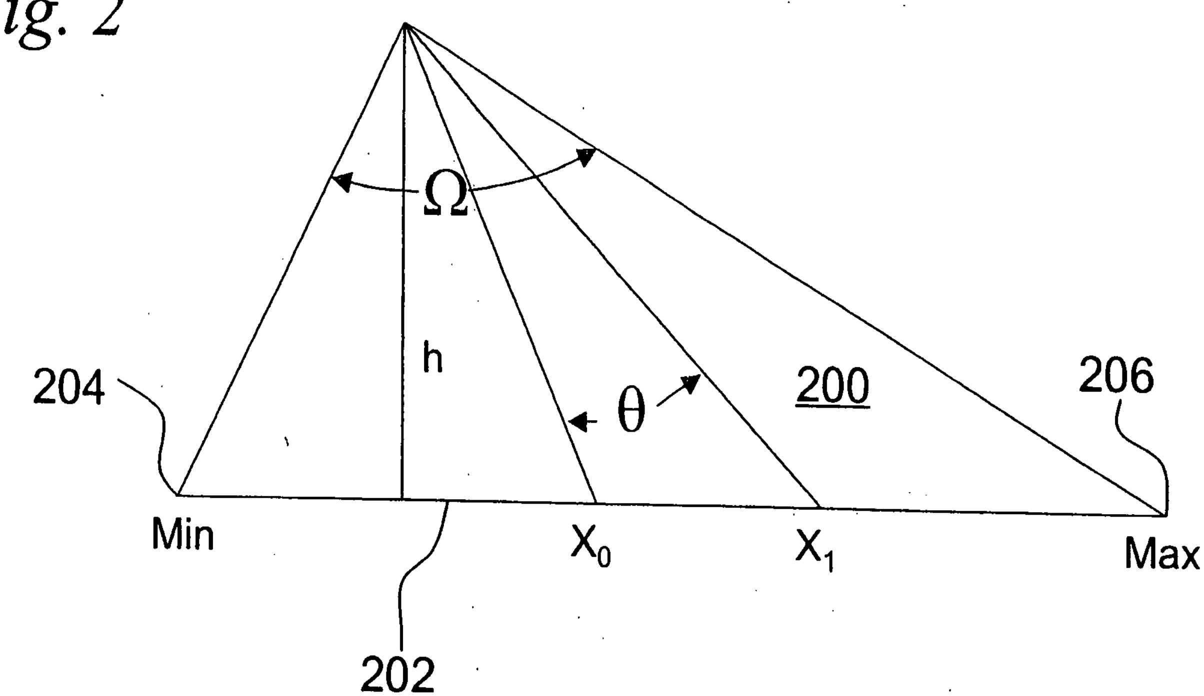
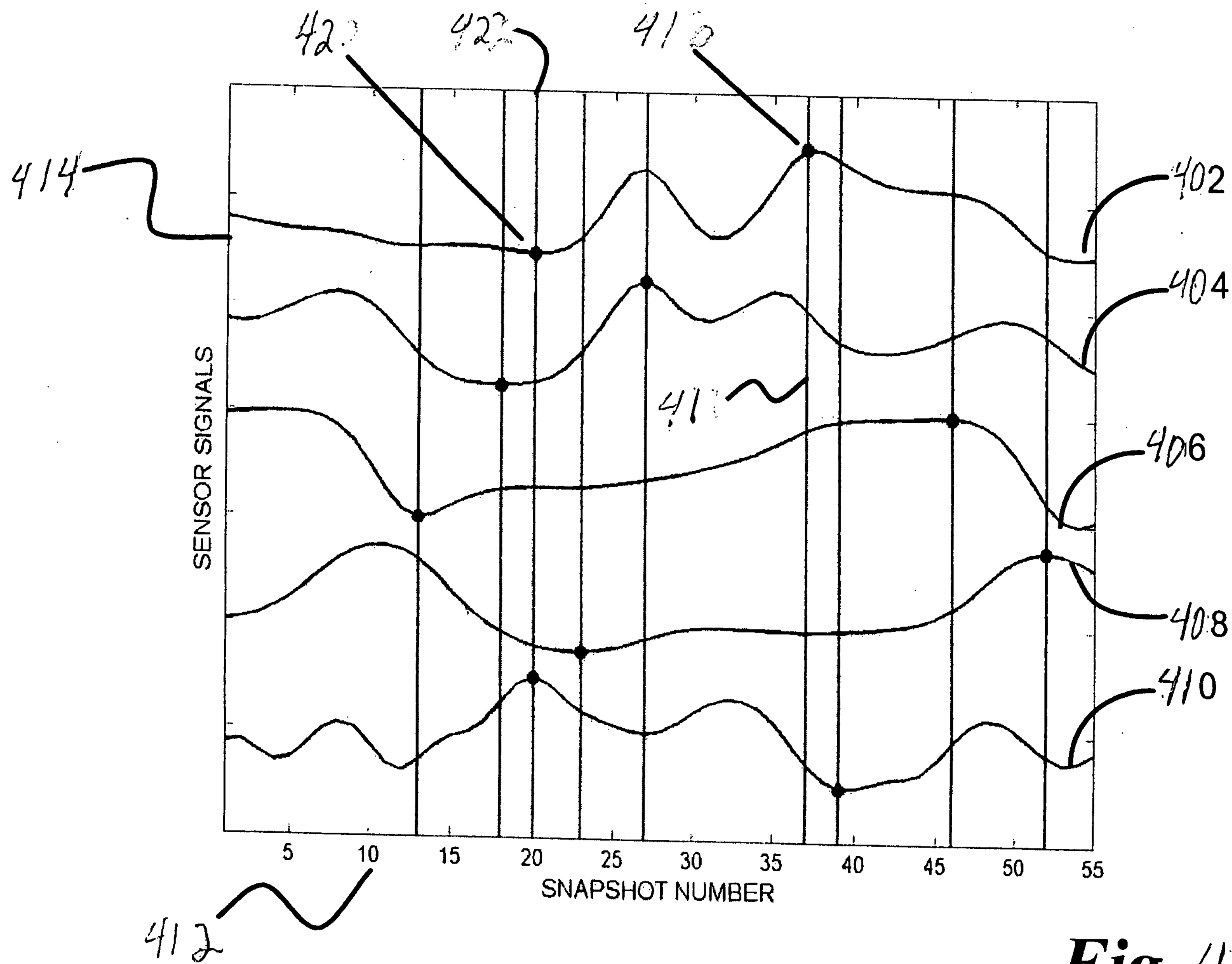
120 South LaSalle Street
Suite 1600
Chicago, Illinois 60603-3406
Telephone 312.577.7000
Facsimile 312.577.7007

Fig. 2




414
402
404
406
408
410
412
SENSOR SIGNALS
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40
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50
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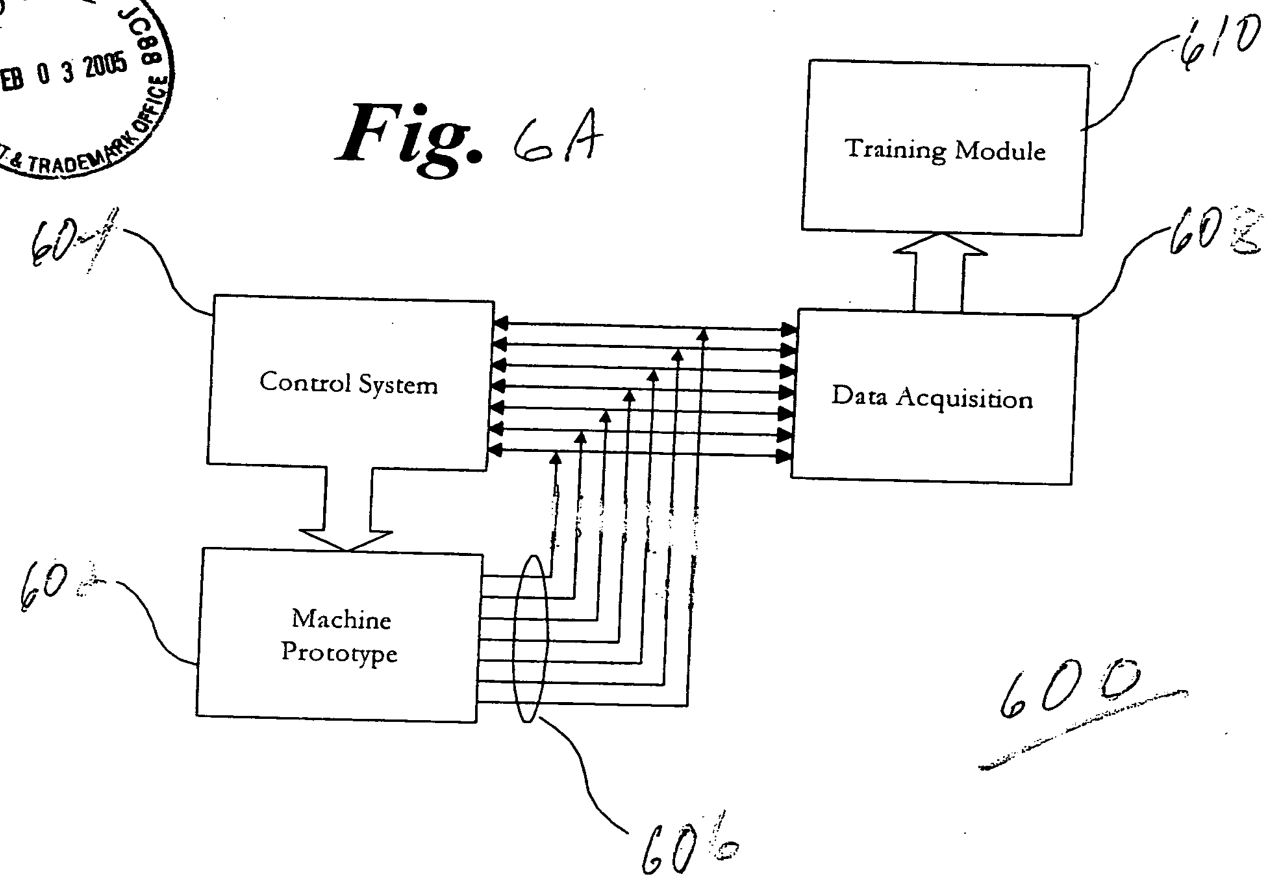
Fig. 4

Fig. 6A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608
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Data Acquisition
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Machine
Prototype
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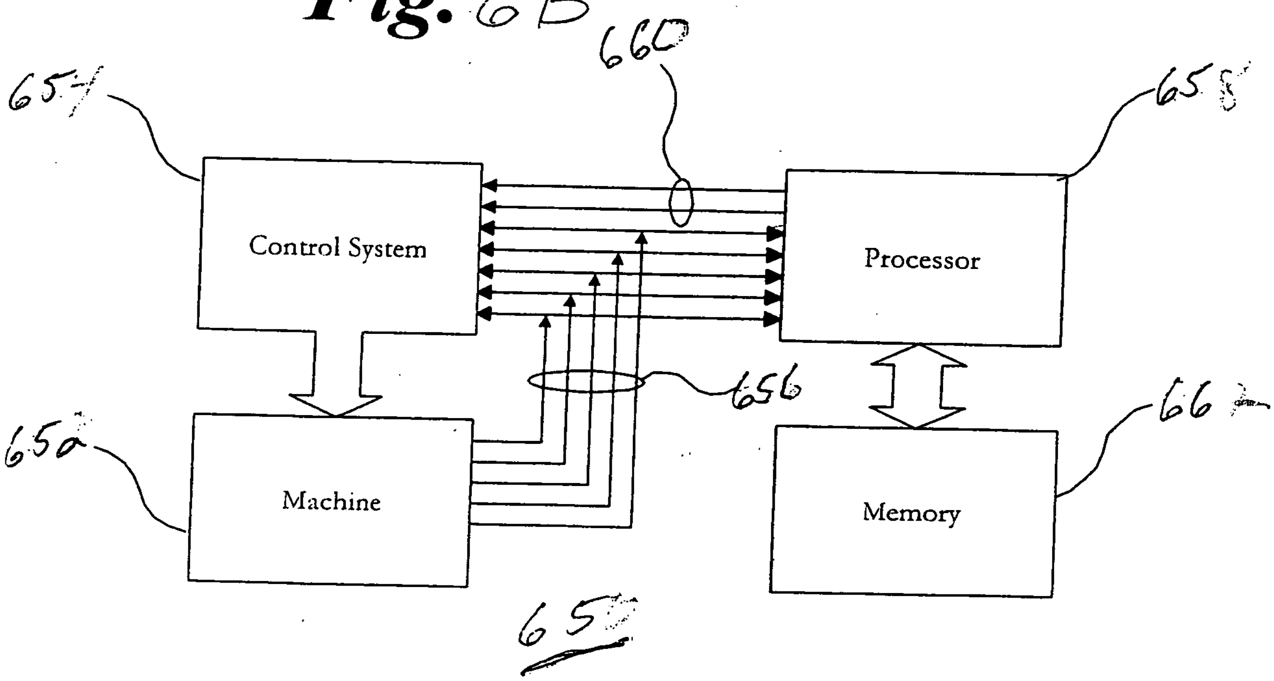
606

Fig. 6B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Processor
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Machine
Memory
650